Trip Table Estimation and Prediction for Dynamic Traffic Assignment Applications

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Outline

- Introduction
  - Dynamic Traffic Assignment (DTA)
  - Pros and cons for DTA models
  - Time-dependent Origin-Destination Demand (TDOD)
- Methodology
  - TDOD demand estimation problem
  - TDOD demand prediction problem
- Results
  - Case study: Victoria Rd Corridor Model
- Incident Management Application
- Conclusion

Introduction: DTA

- Traffic forecasting is a necessary step for efficient network operation and is an integral part of intelligent transportation systems (ITS) applications.
- In the transport domain, dynamic traffic assignment (DTA) models are known as a reliable tool to replicate complex traffic conditions.
- These models are mainly built based on game theory principles. Each traveller attempts to minimize his/her travel cost (time) while their decision impacts the traffic condition other traveller’s decisions to move in the network.

Introduction: DTA - pros and cons

Advantages:

- The intricate traveller route decision can be modelled in the network.
    - User Equilibrium
    - Stochastic route choice (e.g. Logit based models)
- They represent the complicated interaction between users and the network (travellers and roads)

Disadvantages:

- Site-specific models
- Computationally intensive
- Various supply and calibration parameters need to be calibrated

Time-Dependent Origin-Destination (TDOD) Demand

- The most crucial input for any DTA models is the origin-destination (OD) trip table.
- The success of the DTA application relies on the quality of OD demand matrices.
- Estimating the OD demand by using link traffic data is a popular approach and far superior to doing the conventional travel surveys which are slow and expensive.
- Many studies proposed a bi-level optimization formulation where the feedback of demand changes is evaluated by an assignment model iteratively .

TDOD Demand Estimation Problem

We express the problem mathematically as follows:

$$\min \omega . \sum_{i \in I} \sum_{t=1}^{T} (x_i^t - \hat{x}_i^t)^2 + (1-\omega) . \sum_{a \in A} \sum_{t=1}^{T} (y_a^t - \hat{y}_a^t)^2 \qquad \textbf{(1)}$$

$$y_a^h = \sum_{i \in I} \sum_{t=1}^{h} p_{a,i}^{h,t}(X) x_i^t$$

where,

$\hat{x}_i^t$, x_i^t are the initial and estimated demand flow of OD pair i ($i \epsilon I$) at time period t,

$\hat{y}_a^t, y_a^t$ are the observed and estimated link flow in link "*a*" at a time period h ($a \epsilon A$, h=[1,T]),

$p_{a,i}^{h,t}$ is the assignment proportion of x_i^t that passes link "*a*" during a time period h,

ω is the reliability weight on the initial demand data.

TDOD Demand Prediction Problem

The ARIMA model with "p autoregressive terms" and "q moving-average terms" takes the following form:

$$x_i^t = \sum_{l=1}^{p} \varphi^l \, x_i^{t-l} + \sum_{l=1}^{q} \theta^l \, \epsilon^{t-l} + c + \epsilon^t \qquad \textbf{(3)}$$

x_i^t is the estimated demand flow of OD pair i ($i \in I$) at time period t,

$\epsilon^t = x_i^t - \hat{x}_i^t$

The parameters φ^l, θ^l and c are estimated through a least-squares approach.

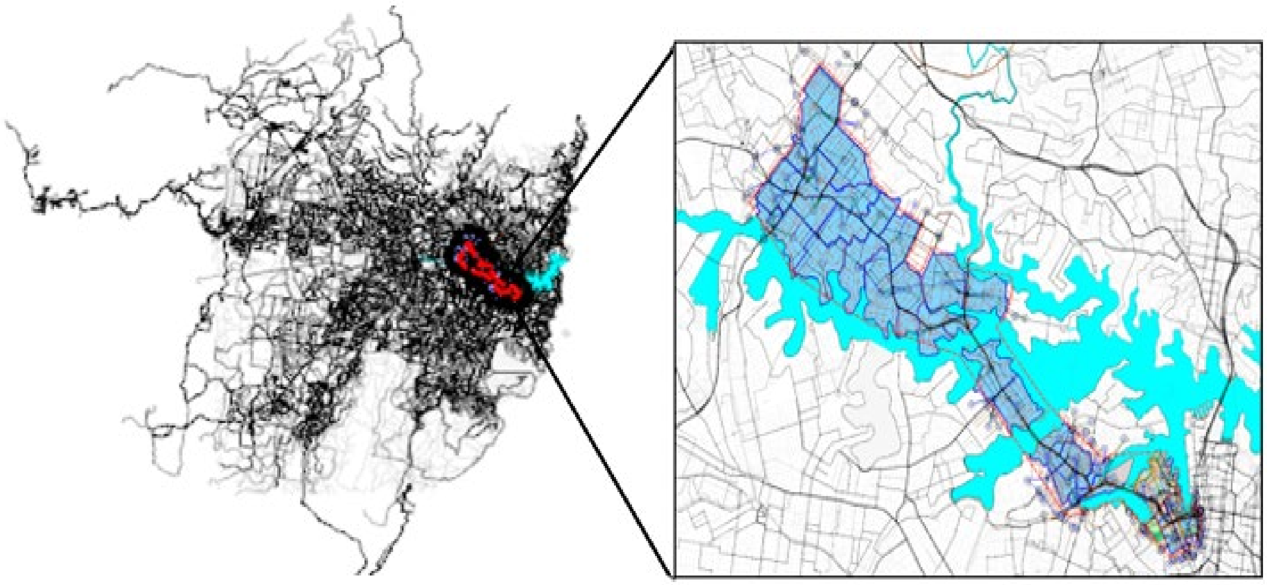
Two ARIMA's characteristics make the application of the model desirable for demand prediction models.

1) the ARIMA regresses demand fluctuation with the lagged demand values.

2) the ARIMA essentially inclines to concentrate on the means and it less digress to the extremes.

Case Study

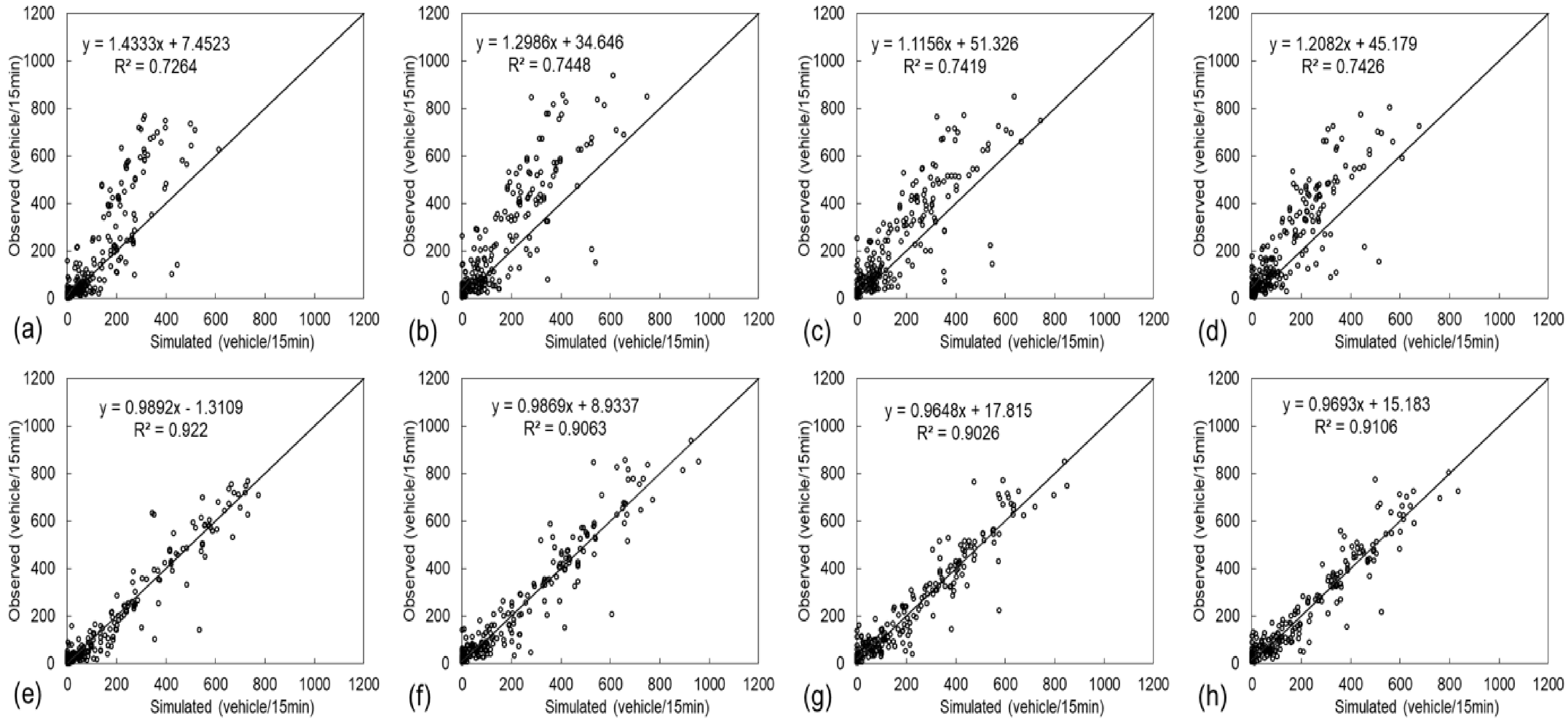
- We evaluate the proposed demand estimation and prediction models for one of the major subnetworks, the Victoria road corridor.
- The initial demand used in this study was obtained from the Sydney Transport Model (STM).
- The spatial configuration of the large-scale Sydney transport network and Victoria corridor are presented



Required transport data

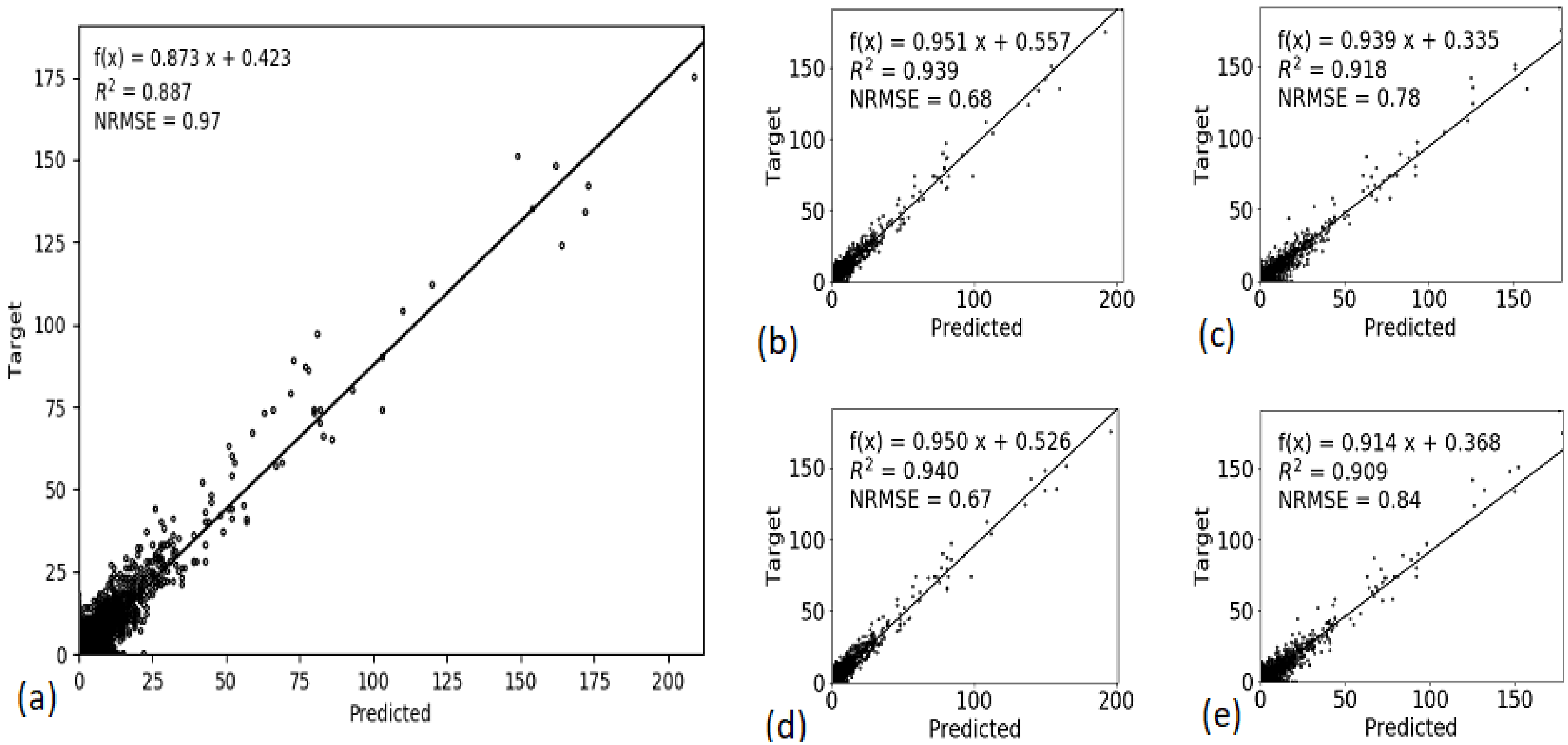
- **Traffic count**: SCATS (arterials) traffic counts,
- **Public transport plans** – using GTFS data,
- **Signal control plans** –using SCATS signal timing,
- **Travellers demand:** Origin-destination of private vehicle users,
- **Incident data logs**: includes the incident location ([x,y] coordinates),
- ....

TDOD Estimation Results



Simulated versus observed traffic volumes in four consecutive one-hour interval; before OD estimation implementation (a) 6:00–7:00 am, (b) 7:00–8:00 am, (c) 8:00–9:00 am, and (d) 9:00–10:00 am. After OD estimation implementation (e) 6:00–7:00 am, (f) 7:00–8:00 am, (g) 8:00–9:00 am, and (h) 9:00–10:00 am.

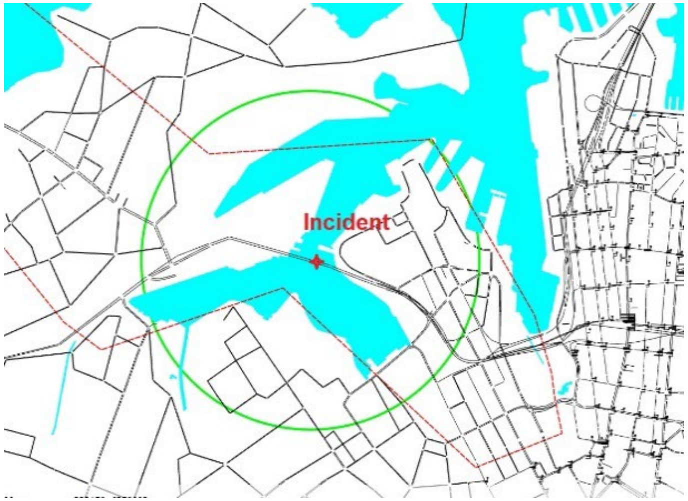
TDOD Prediction Model



Validation of demand forecasting models: (a) no model, ARIMA (b) (1,0,0), (c) (1,1,0), (d) (0,0,1), (e) (0,1,1).

Incident Management Application

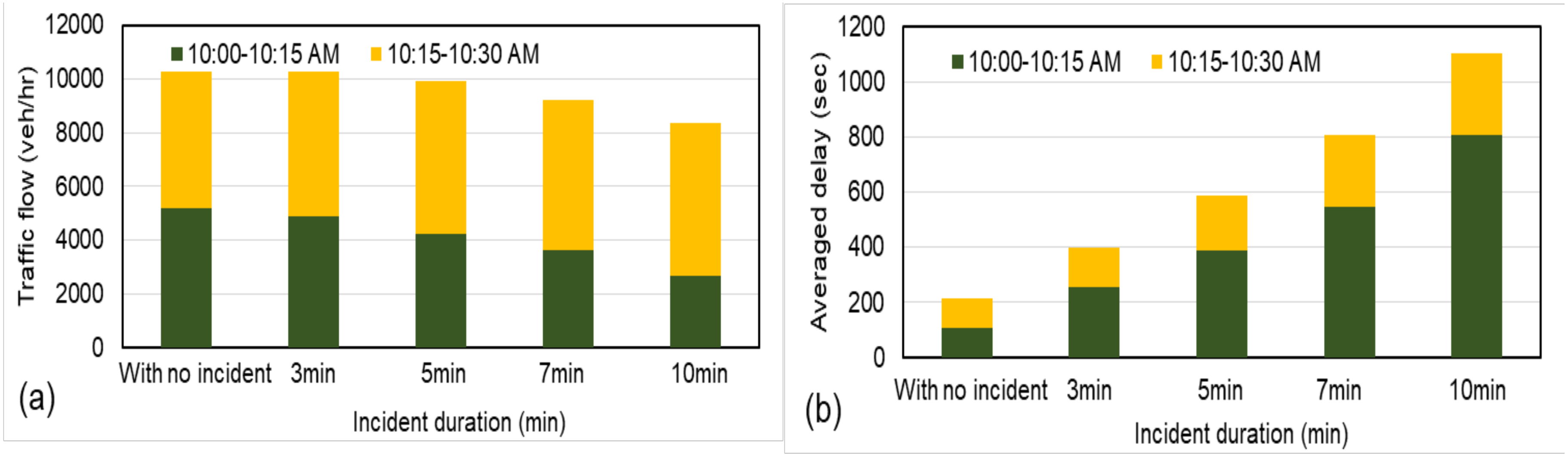
- we employ the proposed OD demand estimation and prediction for an incident analysis application.
- We considered a reported incident on the Anzac Bridge towards the Sydney central business district (CBD).
- Two lanes have been affected by the incident which took place at 09:57 AM. The incident information (location and the number of lanes affected) are transferred to the simulation.
- The demand prediction module is triggered to forecast the demand starting from 10:00 AM for the next half hour.



The configuration of the incident area, Anzac Bridge, Sydney.

Impact of Incident duration on traffic

- The figures present the impact of an incident duration on the traffic flows and network delay.
- We basically simulated what would be the impact on the traffic flow if the incident would last for 3 minutes, 5 minutes, 7 minutes and 10 minutes.



(a) Traffic flow passing through the bridge (b) Averaged delay for travellers in the area.

Conclusion

- This study proposed an efficient OD estimation and prediction approach to reinforce a simulation-based DTA model for operational and planning applications.
- The proposed approach initially calibrates the DTA model based on the most updated archived traffic data and then use it for demand prediction for the next time interval.
- A bi-level dynamic OD demand estimation problem was formulated and solved iteratively.
- The performance of the model was also investigated for the short-term OD prediction. Results show the high capability of the proposed dynamic OD demand estimation to improve the goodness of fit.
- An application of the well-calibrated model (R2 =0.93) is presented to show the applicability of the model for daily network operation purposes under incident circumstances.

THANK YOU!